# CSE 150. Assignment 3

**Out:** *Tue Jul 05* **Due:** *Fri Jul 08 (outside CSE 3214, by 10 am)* **Supplementary reading:** KN, Ch 2.4-2.5.

## 3.1 Conditional independence

For the belief network shown below, indicate whether the following statements of marginal or conditional independence are **true** ( $\mathbf{T}$ ) or **false** ( $\mathbf{F}$ ).



Summer 2016

# 3.2 Noisy-OR



## (a) Conditional probability table

Complete the noisy-OR conditional probability table for the belief network shown above. (The missing values in the table are determined by the ones shown.)

$X_1$	$X_2$	$X_3$	$P(Y = 1   X_1, X_2, X_3)$
0	0	0	0
1	0	0	$\frac{1}{5}$
0	1	0	
0	0	1	
1	1	0	$\frac{2}{5}$
1	0	1	
0	1	1	
1	1	1	$\frac{1}{2}$

### (b) Qualitative reasoning

Suppose that each node  $X_i$  in this model has some finite, non-zero prior probability to be either zero or one; namely  $0 < P(X_i = 1) < 1$ . Sort the following probabilities from smallest to largest:

$$\begin{split} & P(X_1 = 1) \\ & P(X_1 = 1 | Y = 0) \\ & P(X_1 = 1 | Y = 1) \\ & P(X_1 = 1 | Y = 1, X_2 = 0, X_3 = 0) \\ & P(X_1 = 1 | Y = 1, X_2 = 1, X_3 = 1) \end{split}$$

For this part, you are **not** required to compute numerical values for these probabilities, only to sort them in ascending order. In fact, this part can be completed independently of the values in part (a).

### (c) Quantitative reasoning

Suppose that  $P(X_i = 1) = \frac{1}{2}$  for  $i \in \{1, 2, 3\}$ . Compute numerical values for the probabilities in part (b) from these priors and your answers in part (a). Do these values match your previous ordering?

# 3.3 Subsets



Consider the following statements of marginal or conditional independence for the belief network shown above. Indicate the largest subset of nodes  $S \subset \{A, B, C, D, E, F, G, H\}$  for which each statement is true. Note that one possible answer is the empty set  $S = \emptyset$  or  $S = \{\}$  (whichever notation you prefer). The first has been done as an example.

P(A C)	=	$P(A \mathcal{S})$	$\mathcal{S} = \{B, C, E, F\}$
P(A)	=	$P(A \mathcal{S})$	
P(D)	=	$P(D \mathcal{S})$	
P(D A)	=	$P(D \mathcal{S})$	
P(D A,G,H)	=	$P(D \mathcal{S})$	
P(D A, C, E, G, H)	=	$P(D \mathcal{S})$	
P(F)	=	$P(F \mathcal{S})$	
P(G F)	=	$P(G \mathcal{S})$	
P(F,H)	=	$P(F,H \mathcal{S})$	
P(B,E)	=	$P(B, E \mathcal{S})$	
P(H B)	=	$P(H \mathcal{S})$	

# 3.4 Inference in a polytree

Consider the belief network shown below. In this problem you will be guided through an efficient computation of the posterior probability P(F|A, B, D, G). You are expected to perform these computations *efficiently*—that is, by exploiting the structure of the DAG and not marginalizing over more variables than necessary. Justify your steps briefly for full credit.



### (a) Bayes rule

Consider just the part of the belief network shown below. Show how to compute the posterior probability P(C|A, B, D) in terms of the conditional probability tables (CPTs) for these nodes—i.e., in terms of P(A), P(B), P(C|A), and P(D|B, C).



### (b) Marginalization

Consider just the part of the belief network shown below. Show how to compute the posterior probability P(E|A, B, D) in terms of your answer from part (a) and the CPTs of the belief network.



# (c) Marginalization

Consider the belief network shown below. Show how to compute the posterior probability P(G|A, B, D) in terms of your answer from part (b) and the CPTs of the belief network.



## (d) Explaining away

Finally, show how to compute the posterior probability P(F|A, B, D, G) in terms of your answer from parts (b,c) and the CPTs of the belief network.

